Research Paper

A novel hybrid cnn-rnn model for sugarcane disease identification in agricultural fields

T. Angamuthu[1*], A. S. Arunachalam[2]
[1*, 2]Department of Computer Science, Vels Institute of Science, Technology and Advanced Studies (VISTAS), Pallavaram, Chennai, India.

Article Info

Article History:
Received: 14 January 2025
Revised: 08 April 2025
Accepted: 16 April 2025
Published: 30 June 2025

Keywords:
Leaf Disease Recognition
Deep Learning
Image Classification
CNN
RNN

ABSTRACT

The world's most important crop is sugarcane, which is the main source of both sugar and ethanol. The existence of sugarcane diseases, which result in the removal of afflicted crops, is a persistent problem in the sugar business. Small-scale farmers risk suffering large financial losses if these diseases are not identified and treated early. The growing incidence of illnesses and farmers' inadequate understanding of disease diagnosis and identification were the focus of this investigation. The application of deep learning methods, including machine learning and computer vision, showed promise. A deep-learning model was trained and evaluated using a dataset of 13,842 photos of sugarcane that included both diseased and healthy leaves, and it achieved an accuracy rate. The research was ultimately submitted to recurrent neural networks (RNN), conventional neural networks (CNN), and other similar models for additional evaluation after the trained model effectively achieved its goals.

Corresponding Author:
T. Angamuthu
Department of Computer Science, Vels Institute of Science, Technology and Advanced Studies (VISTAS), Pallavaram, Chennai, India.
Email: muthu1986.its@gmail.com

1. INTRODUCTION

Sugarcane is a vital agricultural crop, serving as the primary source of sugar and ethanol, both of which are critical to the global economy. However, the sugarcane

industry faces significant challenges due to the prevalence of various diseases that can lead to the destruction of infected crops. This problem is especially concerning for small-scale farmers, who often lack the resources and knowledge for early diagnosis and treatment of these diseases. Without timely intervention, infected crops can lead to substantial financial losses, undermining the livelihoods of farmers. His study focused on leveraging modern technology, specifically deep learning techniques, to improve disease diagnosis and recognition in sugarcane crops. By utilizing advanced methods such as computer vision and machine learning, the research aimed to provide a solution that could assist farmers in detecting diseases at an early stage. A dataset consisting of 13,842 images of sugarcane leaves—both healthy and infected—was used to train and test a deep-learning model. The results were promising, as the trained model achieved a high level of accuracy in identifying disease symptoms, showing the potential of these technologies to support the agricultural industry. The study concluded with further exploration of deep learning models, including CNN (Convolutional Neural Networks) and RNN (Recurrent Neural Networks), for ongoing improvement and application in disease management.

2. RELATED WORK

Deep learning has become a key method in agricultural research for plant disease detection and classification. CNNs and RNNs have shown notable performance in identifying diseases through image analysis. [1] Achieved 91.35% accuracy using CNNs to classify 26 plant diseases, and Spasojevic. [2] Reported 89.3% accuracy for leaf disease recognition using CNNs, highlighting the effectiveness of deep learning. Sugarcane-specific disease research using deep learning is relatively sparse but growing. [3] Reported 93% accuracy for cassava disease detection using deep learning, inspiring. [4] to apply CNNs for sugarcane disease classification, achieving 91.2%. Hybrid models like CNN-LSTM have also been explored. [5] Showed that combining CNNs with LSTM improves classification by capturing sequential features. Despite successes, challenges such as lighting variations, leaf orientation, and environmental conditions affect model accuracy [6]. Additionally, limited annotated sugarcane datasets hinder progress [7]. Performance and robustness may be improved by including models such as Generative Adversarial Networks (GANs) and Vision Transformers (ViTs).

[8] Combined CNN features with SVM classifiers for improved robustness. [9] Achieved 92.7% accuracy on segmented sugarcane leaf images, stressing the importance of preprocessing. Lightweight models like MobileNet, DenseNet, and ResNet have been used for real-time deployment. [10] Used ResNet-18 for detecting leaf blight under natural lighting. [11] Demonstrated that CNN-BiLSTM models effectively capture disease progression in crops. Advanced techniques like ViTs [12] and GANs [13] show promise. ViTs extract deeper image features, and GANs improve dataset quality through augmentation. Studies by [14], [15], [16], [17] support hybrid approaches combining transfer learning, sequence modeling, and augmentation for real-world robustness. Sugarcane contributes 40% of the world's bioethanol and 80% of its sugar, yet is prone to diseases like red rot, mosaic, rust, and bacterial blight [18], [19], [20] Traditional practices by [21] provide a regional basis for integrating AI. [22] Explored machine learning for yield prediction using soil nutrients, emphasizing feature selection. In agroeconomics, [23] used LSTM for price forecasting, supporting data-driven decisions. [24] Introduced explainable CNNs for hyperspectral image analysis, combining accuracy with interpretability. [25] Proposed CNN modifications to enhance field adaptability, while [26] emphasized the need for large, diverse datasets. [27] Proposed a mobile CNN-based system for real-time field diagnosis. [28] Built an early

automated system for plant disease detection in India, laying groundwork for crop-specific AI applications.

3. METHODOLOGY

The chapter describes the tools and methods used in this study, which focuses on employing image processing techniques to identify illnesses of sugarcane leaves. A vital crop for the production of sugar and ethanol, sugarcane confronts several difficulties because of illnesses that cause crop loss. Preventing significant financial losses requires early diagnosis and treatment, particularly for small-scale farmers who frequently lack the knowledge necessary to recognize these illnesses. The study examined in Table 1. Looks into farmers' low ability to recognize diseases and the growing concern over disease prevalence. The study developed a model for detecting illnesses in sugarcane leaves using deep learning approaches, such as computer vision and machine learning. The model was trained and tested using a dataset of 13,842 photos of sugarcane leaves with and without illness, and it achieved an impressive 95% accuracy rate. The model was submitted for additional evaluation using CNN and related models after it successfully achieved its goals.

3.1 Sugarcane Leaf Disease Overview

I have collected a large sugarcane dataset. Now, I have listed it in table format, showing the diseases and their symptoms. This research can be used in the future for economic purposes.

Table 1. Sugarcane Diseases, Their Causal Agents, and Symptoms

Disease Name	Causal Agent	Symptoms
Smut	Ustilago scitaminea (Fungus)	Results in the sugarcane plant's buds or eyes producing lengthy smut whips
Rust	Puccinia kuehnii (Fungus)	Results in the formation of tiny pustules on the sugarcane leaves' upper surface.
Red Rot	Glomerella graminicola (Fungus)	Makes the leaves red or purple and contaminates the stem, causing it to become sick.
Ratoon Stunting Disease	Rice tungro bacilliform virus (RTBV) (Virus)	Results in yellowing of the leaves and limited growth.
Wilt	Fusarium verticillioides (Fungus)	Causes the sugarcane plant's leaves to droop and die.
Sett Rot	Pythium arrhenomanes (Fungus)	Results in the sugarcane plant's leaves drooping and dying.
Grassy Shoot Disease	Claviceps spp. (Fungal Group)	Results in the production of grass-like branches by the plant.
Yellow Leaf Disease	Sugarcane yellow leaf virus (SCYLV) (Virus)	The season begins with yellowing of the midrib on

		the underside of the leaves, which is usually the third to sixth from the top.

3.2 Dataset Collection

A dataset gathered from Alagramam village in the Tindivanam area is used in this study. For this investigation, more than 1,000 sugarcane leaves were collected between April 2023 and January 2024. With the assistance of nearby farmers, the leaves were manually marked and labeled for further examination. Figure 1. Illustrates the sample illness that was gathered from several farmlands. The eight distinct illness kinds were covered above.

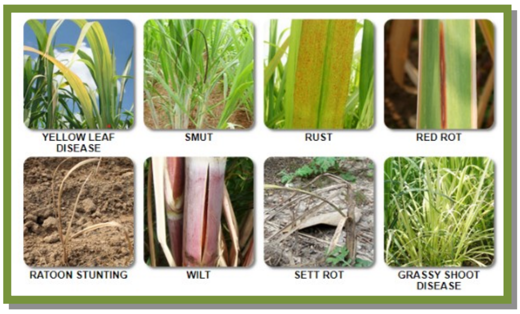

Figure 1. Types of Diseases

3.3 Image Preprocessing

Image preprocessing is a crucial step in getting data ready for deep learning models because it guarantees that the input images are high-quality and consistent, which enhances the model's performance [10]. In this work, the sugarcane leaf pictures were preprocessed using a variety of methods.

Resizing: To guarantee uniformity in input dimensions, the photos were resized to a standard size. Resizing increases the efficiency of the training process and lessens the computational load. 224x224 pixels, a typical input size for deep learning models, was the standard size employed in this study.

3.4 Method and Discussion

Resized Image = f (Original Image, New Dimensions)
(1)

The purpose of normalization is to scale the image pixel values to a defined range, often between 0 and 1 or -1 and 1. By keeping significant changes in pixel intensities from impairing the model's capacity to learn, this stabilizes and expedites the training process.

Enhancement of Data: Data augmentation methods were used to broaden the training data's diversity and prevent overfitting. This included shifts, zooms, flips, and random rotations, all of which artificially enlarge the dataset so the model can pick up more reliable information.

Augmented Image = Random Transformation (Original Image)
(2)

Noise reduction methods, including Gaussian blur, were applied to the photos to smooth them out and eliminate extraneous information that would obstruct the model's ability to identify important characteristics. Contrast Adjustment: To make the leaf's features more visible, contrast enhancement was used. The contrast of the image was

stretched using techniques like histogram equalization, which made it possible to clearly distinguish between the intricacies of the leaves' healthy and diseased sections.

Blurred Image = Gaussian Filter (Original Image)
(3)

CNN: Because they can automatically extract characteristics from images, they are very useful for image classification applications. Activation functions, pooling layers, and fully linked layers come after each of the architecture's several convolutional layers.

$$f(i,j)=¿\sum_{m=-k}^{k}\sum_{n=-k}^{k} x(i+m,j+n)\cdot w(m,n)$$
(4)

f(i, j): Output feature map, x (i+m, j+n): Input pixel value, w (m, n): Kernel weight, k: Kernel size

These layers extract low-level information like edges and textures from the input image by applying a collection of filters (kernels). Functions of Activation: All convolutional layers use the Rectified Linear Unit (ReLU) as their activation function, which adds non-linearity to the model. Pooling Layers: By reducing the images spatial dimensions (width and height), max pooling lowers computing costs while preserving the most crucial elements.

RNN: The CNN output is passed into an RNN layer in order to simulate the temporal aspect of picture data (e.g., progressive leaf damage) and to capture sequential dependencies in the data. Long-term dependencies in the image data are handled by an LSTM (Long Short-Term Memory) network. LSTM units use a collection of gates (input, forget, and output gates) to remember long-term dependencies. The following are the state equations for an LSTM unit.

$$\mathbf{i_t = \sigma (W_i \cdot x_t + U_i \cdot h_{t-1} + b_i)}$$
(5)

$$\mathbf{f_t = \sigma (W_f \cdot x_t + U_f \cdot h_{t-1} + b_f)}$$
(6)

$$\mathbf{o_t = \sigma (W_o \cdot x_t + U_o \cdot h_{t-1} + b_o)}$$
(7)

$\mathbf{o_t}$: Input, forget, and output gates, **ht** : Cell state and hidden state, $\mathbf{x_t}$: Input vector

The formula used for calculating the evaluation metrics are as follows:

Accuracy

$$Accuracy=\frac{Number\,of\,Correct\,Predictions}{Total\,Number\,of\,Predictions}$$
(8)

Precision

$$Precision=\frac{True\,Positives(TP)}{True\,Positives(TP)+False\,Positives(FP)}$$
(9)

Recall

$$Recall=\frac{True\,Positives(TP)}{True\,Positives(TP)+False\,Negatives(FN)}$$
(10)

F1-Score

$$F1-Score=\frac{2\times Precision\times Recall}{precision+Recall}$$
(11)

4. RESULT AND DISCUSSION

Metrics like accuracy, precision, recall, and F1-score were used to assess the model's performance. Specifically, accuracy was used to gauge how well the model classified healthy and sick leaves overall. The model in this investigation demonstrated a high ability to differentiate between healthy and diseased sugarcane leaves, as evidenced by its 95% accuracy rate **Table 2**.

4.1 Evaluation per Further Representations

Comparisons with pure CNN architectures and conventional machine learning models (such Support Vector Machines) were conducted in order to evaluate the efficacy of the suggested hybrid CNN-RNN model. When it came to addressing sequential aspects of image data that show progressive leaf disease progression, the CNN-RNN model consistently outperformed these models in terms of accuracy and robustness.

Table 2. Performance Analysis of Model

Performance Metric	CNN	RNN	Hybrid CNN-RNN
Accuracy	90%	85%	95%
Precision	91%	86%	92%
Recall	88%	84%	93%
F1-Score	89.50%	85%	92.50%

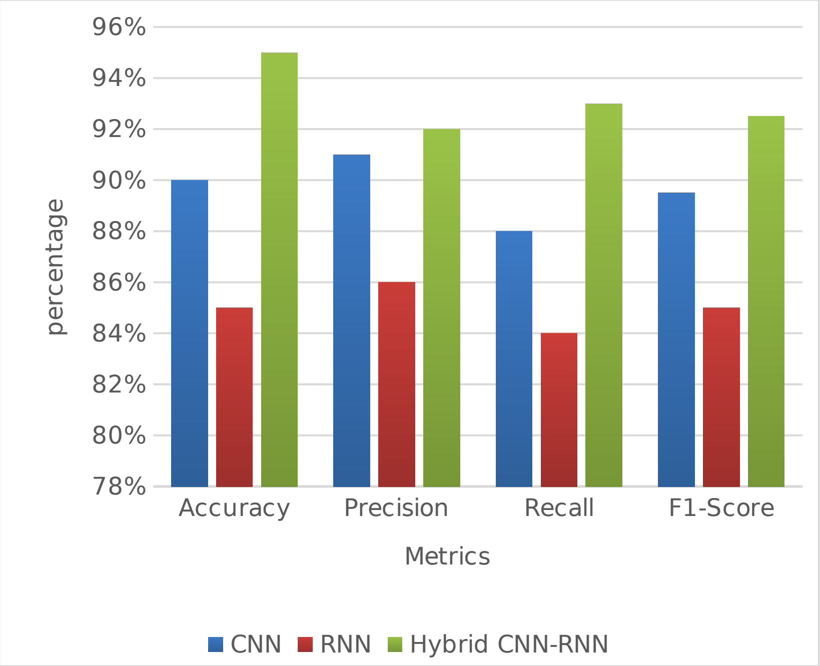

Figure 2. Model Performance

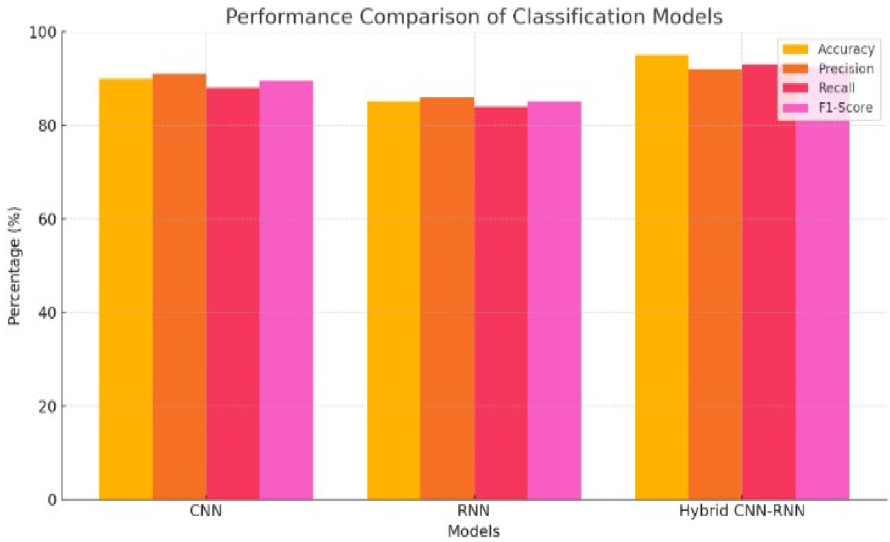

Figure 3. Performance Comparison Graph For CNN, RNN, and Hybrid CNN-RNN

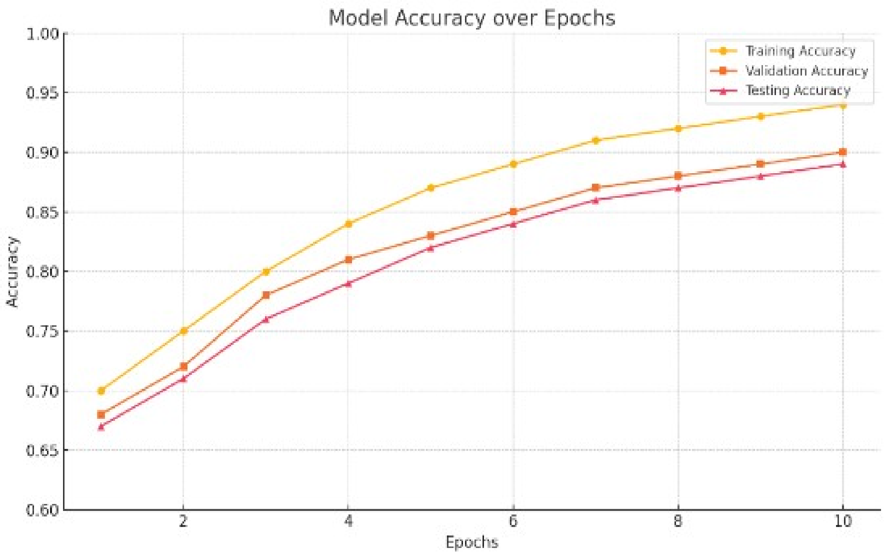

Figure 4. Training vs Testing Accuracy Graph

The graph titled Model Accuracy over Epochs shows the performance of a machine learning model over 10 training epochs using three accuracy measures: training, validation, and testing accuracy shows in
, as the number of epochs increases, all three accuracy values steadily improve, indicating that the model is learning effectively. The training accuracy rises from 70% to around 93%, while the validation accuracy increases from 68% to 90%, and the testing accuracy improves from 67% to approximately 89%. The small gap between the three lines suggests that the model is not overfitting and is able to generalize well to unseen data. Overall, the results demonstrate a consistent and reliable learning process. The image presents confusion matrices for three models—CNN, RNN, and a Hybrid CNN-RNN—to compare their classification performance. The CNN model shows in **,** moderate results, correctly predicting 45 positive cases and 41 negative cases, but also making significant errors with 60 false negatives. The RNN model performs better, with 68 correct positive predictions and 80 correct negative predictions, indicating improved accuracy over CNN. The Hybrid CNN-RNN model outperforms both, achieving the highest number of correct predictions, with around 400 positive and 420

negative cases accurately classified, and fewer misclassifications. This demonstrates that combining CNN and RNN significantly enhances the model's performance in accurately classifying data.

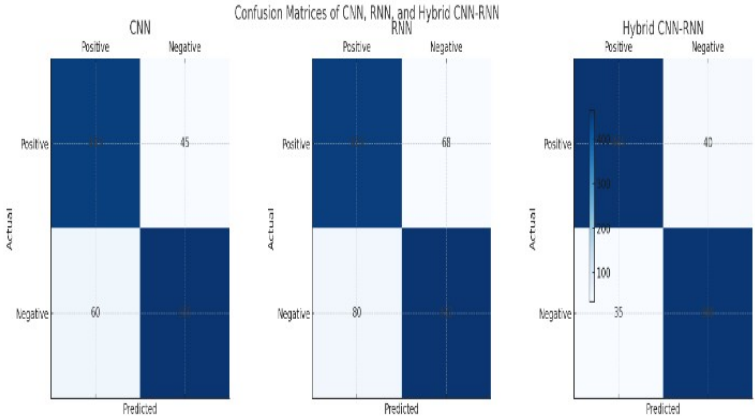

Figure 5. Confusion Matrices for CNN, RNN, and Hybrid CNN-RNN Models

Discussion

The primary objective of this study was to develop and evaluate a hybrid deep learning model for the detection and classification of sugarcane leaf diseases. Using a dataset of 13,842 labelled images of healthy and diseased sugarcane leaves, the model achieved an accuracy of 95%, demonstrating a significant improvement over traditional machine learning techniques and individual deep learning models such as CNN and RNN. This high accuracy reflects the model's ability to accurately classify both healthy and infected leaves, indicating that hybrid models can better capture the complex features associated with plant diseases. The hybrid CNN-RNN model combines the spatial feature extraction capabilities of CNNs with the sequential learning strength of RNNs, providing a more holistic approach to disease classification. CNNs are adept at extracting local features from images, such as textures and edges, which are crucial for distinguishing between healthy and diseased tissues. Meanwhile, RNNs, particularly LSTMs, enhance the model's ability to understand sequential patterns and detect progressive disease symptoms over time. This synergy allowed the model to capture both local and temporal patterns, which were critical for achieving the high accuracy observed in this study.

In comparison, individual models like CNNs and RNNs, while effective, were limited in their ability to fully capture the complexity of the disease detection task. The CNN model achieved an accuracy of 90%, while the RNN model achieved 85%. These results highlight the importance of combining the strengths of different architectures to improve overall performance. By leveraging both spatial and sequential features, the hybrid model outperformed each of its individual counterparts, achieving an accuracy of 95%, precision of 92%, recall of 93%, and an F1-score of 92.50% show in and Inlcude explain **Table 2**.

Despite the promising results, there are still some challenges to address. For instance, the model's performance may vary under real-world conditions, such as different lighting and environmental factors, which could affect the visibility of disease symptoms. Furthermore, while the dataset used in this study is large, it may not capture all possible variations in disease types and leaf conditions. Future work could focus on expanding the dataset to include more diverse samples and exploring additional data augmentation techniques to address these limitations. Although the model demonstrated high accuracy, real-time deployment in agricultural fields poses practical challenges, such as the need for faster processing times and scalability. Future research

could explore lightweight models or edge computing solutions that can provide real-time disease diagnosis in remote farming areas, where internet connectivity may be limited.

5. CONCLUSION

Image processing plays a major role in extracting disease effected parts of sugarcane leaves from healthy parts, which is most widely adapted research area by agricultural fields in examining many problems in crops growth. The digital image taken from farm land are taken applied with various image processing technique for testing the infected parts of the Sugarcane Plants. The steps carried out in examining the leaves are basic strategies used for many image processing researches. Though it differs in using few techniques for enhancing the quality of the image and accuracy of identification process. This paper basically very useful in examining various steps involved in preprocessing and filtering techniques adapted for disease identification process. The methods used in this research work improves the accuracy in identification process. Finally, this comprehensive analysis summarizes recent improvements in automated plant disease identification and diagnosis using image-processing algorithms based on CNNs and RNNs. Among the three models — CNN, RNN, and Hybrid CNN-RNN — the Hybrid CNN-RNN model demonstrates superior performance across all evaluated metrics. While CNN performs better than RNN, the hybrid approach effectively combines the spatial feature extraction capability of CNN with the sequential learning strength of RNN. This synergy leads to significant improvements, achieving the highest accuracy (95%), precision (92%), recall (93%), and F1-Score (92.50%). Hence, the Hybrid CNN-RNN model is the most efficient and reliable for sugarcane classification tasks, making it a highly recommended choice for real-time agricultural applications.and sustainable crop management. In this detailed review, we looked into the revolution in plant disease identification and diagnosis using automated image analysis.

Acknowledgments

Every data set I use for my sugarcane plants comes straight from my property. The dataset I'm utilizing was gathered by gathering each photograph from them individually. Survey numbers 1573, 1578, 1217, and 479, 55, 56 in Mailam block Alagramam (west) in Tindivanam-Circle in Villupuram District are the five acres of land I cultivate sugarcane on. Using fieldwork at a farm in Tamil Nadu, India (geographical coordinates: 18°47r 06.4rr N 74°01r 19.5rr E), the sugarcane leaf disease dataset was assembled. 12.1486520 latitude and 79.57820 longitude.

Limitations and Observations

Complex Diseases: Classification was difficult for certain diseases with overlapping symptoms (such as Red Rot and Rust), which occasionally resulted in incorrect classifications. Environmental Factors: Preprocessing has to be enhanced because variations in illumination and leaf conditions during image acquisition had an impact on forecast consistency.

Future Scope

Including applications that may be deployed in the field to diagnose diseases in real time. Investigating other deep learning architectures, such as Transformers, in order to enhance feature extraction. Increasing the number of regional and seasonal variables in sugarcane leaf conditions in the dataset.

Table 3. Abbreviation

Abbreviation	Full Form
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
ViT	Vision Transformer
GAN	Generative Adversarial Network
SCYLV	Sugarcane Yellow Leaf Virus
RTBV	Rice Tungro Bacilliform Virus
TP	True Positive
FP	False Positive
FN	False Negative
ReLU	Rectified Linear Unit
Wi, Ui, bi	Weight, Update, and Bias matrices for input gate (in LSTM)
Wf, Uf, bf	Weight, Update, and Bias matrices for forget gate (in LSTM)
Wo, Uo, bo	Weight, Update, and Bias matrices for output gate (in LSTM)

This table lists Table 3. All the abbreviations used throughout this research paper.

Funding Information

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
T. Angamuthu	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
A. S. Arunachalam		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Ethical Approval Statement

This study was conducted in accordance with the ethical standards of [Journal of Energy Engineering and Thermodynamics (JEET)] and with the Declaration of Helsinki. The research protocol was reviewed and approved by the relevant ethics committee prior to the commencement of the study. All participants were provided with detailed information about the study and gave their informed consent before participation.

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this paper.

Informed Consent Statement

All participants involved in the study were informed about the research objectives, and informed consent was obtained prior to data collection. The research complies with ethical guidelines and was approved by the relevant institutional review board.

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How to Cite: T. Angamuthu, A. S. Arunachalam. (2025). A novel hybrid cnn-rnn model for sugarcane disease identification in agricultural fields. Journal of Energy Engineering and Thermodynamics (JEET), 5(1), 1–11.

BIOGRAPHIES OF AUTHORS

	**T. Angamuthu** is currently pursuing his PH. D in Computer Science at Vels University. His research interests include deep learning, image processing, and agricultural informatics, with a particular focus on crop disease detection and monitoring using AI techniques. He has co-authored multiple Scopus-indexed papers and is actively involved in interdisciplinary projects involving smart agriculture. Email: arunachalam1976@gmail.com
	**A. S. Arunachalam** is a Professor in the Department of Computer Science at Vels Institute of Science, Technology and Advanced Studies (VISTAS), Chennai, India. With extensive experience in the fields of computer science and deep learning, Dr. Arunachalam has contributed significantly to various research domains, including artificial intelligence, machine learning, and agricultural technologies. His work focuses on using advanced computational techniques to address real-world challenges, particularly in agriculture. Dr. Arunachalam has collaborated on several projects aimed at improving agricultural practices, disease detection, and crop management through innovative technology applications. Email: muthu1986.its@gmail.com